

## Research Article

# The Impact of Urban Sprawl and Smart City Construction on Regional Coordination

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Received 12 January 2021; Revised 31 March 2021; Accepted 10 May 2021; Published 19 May 2021

Academic Editor: Chenxi Huang

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The construction of smart cities has promoted the process of urbanization and sustainable urban sprawl, which may accelerate regional coordination by enhancing the spatial correlation among the cities. Firstly, this paper built the mechanism for the impact of urban sprawl and smart city construction on regional coordination and adopted the corrected night light data as the index of economic measurement, using the dynamic fixed effect spatial Dubin model to test theoretical mechanism. It is found that urban sprawl has strongly promoted the regional coordination, which is especially obvious among the neighboring cities. However, the construction of smart cities is not conducive to regional coordination, only when interacting with urban sprawl. The results of robustness check and endogenous treatment are consistent with the baseline regression. Further research shows that urban sprawl restricts the positive effect of industrial agglomeration but could promote economic growth and regional coordination through smart city construction. The policy enlightenment lies in that smart city construction should be promoted, so as to improve economic growth, and smart city network and urban sprawl should be synchronously promoted to accelerate regional coordination.

## 1. Introduction

China's economic development has achieved remarkable achievements in the process of reform and opening up. However, with the inflow of production factors to the east, the difference among eastern coastal areas and inland areas is gradually widening. More seriously, the location advantage of the eastern area is still potential driving force for attracting production factors (Liu [1]). Meanwhile, the level of urbanization has been rapidly improved, which has led to the continuous expansion of the urban space, experiencing rapid, discontinuous and low-density expansion (Liu et al. [2]). The research shows that China's urban space increased by 43.5% from the year of 2000 to 2010, and the land expansion was significantly faster than the improvement of population, leading to the typical characteristics of increasing urban population and decreasing population density (Jiang and Xi [3]). Figure 1 shows the mutative trend

of urbanization rate and regional difference from 1978 to 2018. It could be found that the urbanization level increased rapidly after 1998, while regional differences tended to be flat around 1998, which shows obvious downtrend around (2004).

This paper focuses on the relationship between urban sprawl and regional coordinated development based on the impact of smart city construction. Smart cities are formed by the continuous development and evolution of digital cities. It is an inevitable stage for the level of urbanization rising to a certain degree, which has become an important driving force for the development of urbanization in China (Lv et al. [4]). The path of smart city construction is to improve human resources, information infrastructure, and urban innovation capabilities. Through the widespread use of smart application platforms, the government's urban management capabilities and service levels could be improved, which could connect different regions and promote the spread of urban

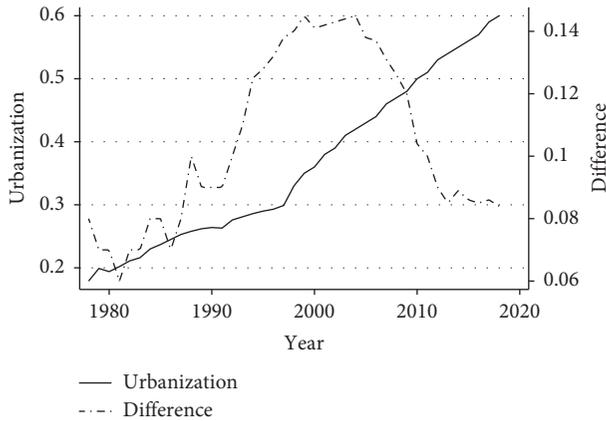


FIGURE 1: The evolution trend of urbanization rate and regional differences from 1978 to 2018.

space (Lu and Yang [5]). We try to explore how smart city construction affects the process of urban sprawl, and the impact of urban sprawl and smart city construction on regional coordination.

The remainder of the study is organized as follows. Firstly, we intend to review the relevant literature on smart city, urban sprawl, and regional coordination systematically. Secondly, we explain the mechanism of how smart city construction affects urban sprawl, which might promote regional coordination. Thirdly, based on the process of modifying the urban night light data, we intend to measure the level of urban sprawl combined with LandScan population dynamics statistics. Fourthly, we intend to use spatial Durbin dynamic panel model with fixed effect for empirical analysis, and urban surface roughness is used for endogenous treatment. Finally, robustness test of the empirical results is conducted, and we try to interpret the mechanism between urban sprawl and regional coordination by mediating effect test through dynamic industrial agglomeration.

## 2. Literature Review

With the rapid development of new generation of information technology, the concept of smart city proposed by IBM has become new idea for urban development. Smart city construction has become an important driving force of urbanization in China. It is required not only to solve economic problems in the process of urban development, but also to improve social, cultural, and environmental issues in urban governance. Domestic and foreign research on the evaluation index system of smart city construction mainly focuses on the dimensions of network and other infrastructure, economic development and industrial adjustment, social management and services, and value guidance and realization (Xu et al. [6]). Chen et al. [7] found that smart city is formed by key elements such as organization, technology, governance, policy environment, communities, economy, infrastructure, and natural environment. Smart city construction is required to provide efficient governance and service systems, upgraded

industrial structure, and comfortable and superior living environment (Chourabi et al. [8]; Alawadhi et al. [9]).

The phenomenon that goes hand-in-hand with the construction of smart cities is urban sprawl. Urban sprawl is featured by dynamic evolution of urban spatial structure, manifested by the feature of geographical space expansion and population density decrease, making the urban structure more decentralized and polycentric (Glaeser and Khan [10]). Liu et al. [2] explained the causes of urban sprawl from the perspective of market uncertainty. Due to spatial dispersion of elements and decreasing level of industrial agglomeration, urban sprawl may incur efficiency losses (Lee and Gordon, [11]). The literatures are also more inclined to support the conclusion that urban sprawl may restrict the process of production efficiency improvement or economic growth. The mechanism lies in the decline of industrial agglomeration caused by sprawl, which intends to increase the cost of “face-to-face” communication (Fallah et al. [12]; Farber and Li [13]; Di Liddo [14]; Qin and Liu [15]). Therefore, the positive effect of industrial agglomeration is weakened. However, for cities with too large scale, which may lead to uneconomic agglomeration, urban sprawl could reduce the production cost and housing cost in turn, which is conducive to economic or productivity improvement. In addition, some studies focused on public welfare, and ecological environment under the influence of urban sprawl (Sun and Wan [16]; Jiang [17]).

Since urban sprawl and smart city construction could change the spatial distribution of elements and accelerate the flow of elements, it could be inferred that the process attaches impact on regional coordination. The literatures of research on regional coordination have accumulated plentiful achievement, among which different results are presented. In the early studies, it is intended to believe that there is no convergence throughout the whole country, showing conditional convergence, or club convergence (Lin and Liu [18]; Xu and Li [19]). In recent years, it is more likely to agree that there is stronger convergence across the country. The characteristics of club convergence are prominent due to the development of urban agglomerations (Tan et al. [20]; He and Chen [21]). However, few studies believe that there is no obvious convergence in China, among which expansion of differences exists (Shi and Ren [22]). With the application and development of spatial methods, most studies need to consider spatial spillover effects among the regions. It is found that the regions showed stronger convergence trend under the condition of spatial effect. Ignoring spatial effect may even lead to diametrically opposite conclusions. In addition, the research on regional productivity synergy emerged in the latest years, with the increasing contribution of total factor productivity on economic growth (Yu [23]).

Through literature review, we find that smart city construction is the type of upgraded urbanization, and how could urban sprawl and smart city construction affect regional coordinated development needs more evidence and further explanation. The following parts focus on the mechanism about the impact of urban sprawl and smart city construction on regional economic coordination, and the empirical test based on the city-level data.

### 3. Mechanism Model

The theoretical model on the impact of urban sprawl on economic convergence is built based on the neoclassical growth model, which is expanded by the model of Mankiw et al. [24] and López et al. [25]. Firstly, the simple economic growth model could be expressed as

$$Y(it) = A(it)K(it)^{\tau_k}H(it)^{\tau_h}L(it)^{1-\tau_k-\tau_h}, \quad (1)$$

in which  $\tau_k$  and  $\tau_h$  indicate the share of physical capital and human capital, respectively. There is spatial spillover effect on the economic growth of cities and neighboring spatial units, and there are centripetal force and centrifugal force featured by nonlinear change among the cities, which could affect the spatial balance. We assume that technology  $A(it)$  with shared characteristics depends on the technology level of the cities and neighboring areas, and as the scale of neighboring cities expands, the spillover effect presents a nonlinear change among the cities. It could be expressed as

$$A(it) = \Delta_{it} \left( k_{pit}^{\tau_k} h_{pit}^{\tau_h} \right)^{s^y}, \quad (2)$$

in which  $\Delta_{it}$  indicates the exogenous parameters, and  $k_{pit}$  and  $h_{pit}$  indicate the unit physical capital and human capital of adjacent spatial areas, respectively.  $s^y$  indicates the spatial spillover effect, in which  $s$  represents the level of urban sprawl, and  $y$  indicates the level of urban intelligence. Both sizes are between (0, 1). We can derive model (3) by putting (2) into (1), which is expressed as

$$y(it) = \Delta_{it} k(it)^{\tau_k} h(it)^{\tau_h} \left( k_{pit}^{\tau_k} h_{pit}^{\tau_h} \right)^{s^y}. \quad (3)$$

According to the equilibrium of the neoclassical growth model, we derive the following formulas (4) and (5):

$$g_k = \frac{\dot{k}}{k} = s_k k^{-(1-\tau_k)} h^{\tau_h} k_p^{s^y \tau_k} h_p^{s^y \tau_h} - (n + g + \delta), \quad (4)$$

$$g_h = \frac{\dot{h}}{h} = s_h k^{\tau_k} h^{-(1-\tau_h)} k_p^{s^y \tau_k} h_p^{s^y \tau_h} - (n + g + \delta), \quad (5)$$

in which  $n$  indicates the population growth rate, and  $g$  indicates technological progress.  $s_k$  and  $s_h$  indicate the output share of physical capital and human capital, respectively, and  $\delta$  indicates the capital depreciation rate. When  $\dot{k}(t)$  and  $\dot{h}(t)$  are equal to zero, and the hypothesis of  $\tau_k + \tau_h < 1$  is satisfied simultaneously, the steady-state capital stock  $k^*$  and  $h^*$  could be deduced as

$$k^* = \left( \frac{s_k^{1-\tau_k} s_h^{\tau_h} k_p^{s^y(1-\tau_k)} h_p^{s^y \tau_h}}{n + g + \delta} \right)^{1/(1-\tau_k-\tau_h)}, \quad (6)$$

$$h^* = \left( \frac{s_k^{\tau_k} s_h^{(1-\tau_k)} k_p^{s^y \tau_k} h_p^{s^y(1-\tau_k)}}{n + g + \delta} \right)^{1/(1-\tau_k-\tau_h)},$$

and formula (7) could be derived, combining with formula (3):

$$y^* = \left( \frac{s_k^{\tau_k} s_h^{\tau_h} k_p^{s^y \tau_k} h_p^{s^y \tau_h}}{(n + g + \delta)^{\tau_k + \tau_h}} \right)^{1/(1-\tau_k-\tau_h)}. \quad (7)$$

It is derived that the per capita output that reaches the long-term equilibrium state is related not only to the share of capital gains, but also to the share of capital in neighboring units and  $s^y$  which is used to measure the impact of the size of neighboring cities. According to the neoclassical growth model, the relationship between actual average output and steady-state output could be expressed as

$$\frac{d \ln(y(it))}{dt} = \lambda [\ln(y^*(it)) - \ln(y(it))], \quad (8)$$

in which  $\lambda = (n + g + \delta)(1 - \tau_k - \tau_h)$ .

The economic growth equation could be expressed as formula (9), which is Taylor expansion of formula (8):

$$\ln(y(it)) - \ln(y(0)) = \varepsilon - \frac{(1 - e^{-\lambda t})s^y}{1 - \tau_k - \tau_h} \ln y(0) + \frac{(1 - e^{-\lambda t})s^y}{1 - \tau_k - \tau_h} y_p(0) + s^y g_{y_p} + \frac{(1 - e^{-\lambda t})}{1 - \tau_k - \tau_h} [\tau_k (\ln s_k + \ln(n + g + \delta))] + \tau_h (\ln s_h + \ln(n + g + \delta)), \quad (9)$$

in which  $\varepsilon = (1 + s^y)g - (1 - e^{-\beta t})(1 - s^y/1 - \tau_k - \tau_h)$  ( $\ln \Delta_0 + gt$ ).

According to  $(1 - e^{-\lambda t})s^y/1 - \tau_k - \tau_h$  in formula (9), we could draw the proposition that the convergence trend could be strengthened together by urban sprawl and the smart city construction.

## 4. Data, Indicator, and Modeling

**4.1. Data.** Gross domestic product (GDP) is an important indicator that is used to measure economic development or growth. However, the biggest limitation lies in the statistical comparison among the regions. In addition, local officials

may have strong incentives to falsify data under China's administrative assessment system linked to GDP. Thus, some research began to use the global night light data released by the National Oceanic and Atmospheric Administration (NOAA), in order to achieve the comparability and reflect the level of economic development (Henderson et al. [26]). NOAA has published data from 1992 to 2013, including the satellites of F10, F12, F14, F15, F16, and F18, forming a total of 34 images, as well as thirty-four data images. The spatial light resolution is 30 seconds, and the gray value interval is (0, 63). The data needs to be corrected since the original night lights are not stable, and there are two sets of satellite observation data in some years. We take the average value when there are different satellite observations, and we uniformly set the value as zero when the satellite DN observation value is zero in any year, attributed to the abnormal fluctuation of light.

Due to the large instability of night light data, there are two sets of light data in individual years. The data needs to be corrected concerning the aging and switching of observing satellites may reduce the comparability of data in different years.

*4.1.1. Baseline Correction.* Since the light data is observed by multiple groups of satellites, it is necessary to set reference point for mutual correction. We take the city of Hegang in Heilongjiang province as the reference area and take the data of F18 satellite as the benchmark. The correction model is expressed as

$$SP_i = 0.5 * (LP_i - HP_i) + 0.5. \quad (10)$$

The values of  $a$ ,  $b$ , and  $c$  could be simulated by equation (10), in which  $DN_{HG, F18-2013}$  represents the Hegang grid value observed by the F18 satellite in 2013, while  $DN_{HG, F-T}$  indicates Hegang grid values observed by different satellites in other years. Through the equation, thirty-three estimated values of  $a$ ,  $b$ , and  $c$  could be obtained, to bring the estimated values  $a$ ,  $b$ , and  $c$  into function (11) composed by the independent variables of the F18 observations of different cities in 2013, so as to obtain the corrected light values.

*4.1.2. Outlier Value Handling.* Since there are two sets of satellite observations in specific year, it could be treated by taking averaging value. In addition, the value is set as zero if the DN value is zero, even if another group of observing satellites shows nonzero value. The reason lies in that another set of nonzero value might be caused by abnormal fluctuations.

## 4.2. Indicator

*4.2.1. Urban Sprawl Indicator.* Referring to the method of Fallah et al. [27], the index for measuring urban sprawl is set as follows:

$$SP_i = 0.5 * (LP_i - HP_i) + 0.5, \quad (11)$$

in which  $LP_i$  is the ratio of population density, which is lower than the national average density, while  $HP_i$  represents the ratio of the population density that is higher than the national average density. However, it is necessary to concern land expansion since urban sprawl is reflected not only in population expansion, especially under the background that the land urbanization is faster than population urbanization in China. Thus, we further modify the urban sprawl index as follows, referring to Qin and Liu [15]:

$$SA_i = 0.5 * (LA_i - HA_i) + 0.5, \quad (12)$$

in which  $LA_i$  is the ratio of land density, which is lower than the national average density, while  $HA_i$  represents the ratio of the land density that is higher than the national average density. The new indicators for urban sprawl could be further synthesized based on equations (11) and (12):

$$Sprawl_i = \sqrt{SP_i * SA_i}. \quad (13)$$

The urban sprawl value interval constructed by equation (13) is (0, 1), and the closer the value to 1, the higher the sprawl level. LandScan global population dynamics statistics provide valuable dataset for obtaining the population distribution since there is no detailed domestic population data in the cities. In addition, we integrated the two databases of night light data and LandScan global population dynamics data, so as to extract grids with DN value greater than 10 and population density greater than 1000 people/km<sup>2</sup>.

*4.2.2. Dynamic Industrial Agglomeration.* We incorporate the urban geographic area into the construction of agglomeration index, in order to reflect the impact of urban sprawl. In addition, the level of industrial agglomeration should also be reflected in the process of firms' entering or exiting, since the research is usually limited to the stock level when constructing industrial agglomeration indicators. The industrial agglomeration index is built as follows.

*Step 1.* Taking the firms  $f$  in different industries added up to the city-industry level from three dimensions of labor, capital, and output and then divided by geographic area so as to obtain the spatial intensity in city-industry dimensions, the formula could be formed as

$$\begin{aligned} de_{cit} &= \sum_f \frac{\text{employment}_{fcit}}{\text{area}_{ct}}, \\ da_{cit} &= \sum_f \frac{\text{asset}_{fcit}}{\text{area}_{ct}}, \\ do_{cit} &= \sum_f \frac{\text{output}_{fcit}}{\text{area}_{ct}}, \end{aligned} \quad (14)$$

in which  $c$  represents the city, and  $i$  is the urban industry.  $de_{cit}$ ,  $da_{cit}$ ,  $do_{cit}$  indicate employment, asset, and output, respectively.

*Step 2.* To integrate the process of firms' entry and exit into the index, we use  $(1 + p_{cit})$  as the weight to add up the spatial intensity of the previous year, in which  $p_{cit}$  is the net increase share of industry  $i$ . The formula could be formed as

$$\begin{aligned} ade_{cit} &= (1 + p_{citi}) * de_{cit-1}, \\ ada_{cit} &= (1 + p_{cita}) * da_{cit-1}, \quad \text{and,} \\ ado_{cit} &= (1 + p_{cito}) * do_{cit-1}, \end{aligned} \quad (15)$$

in which  $p_{citi}$ ,  $p_{cita}$  and  $p_{cito}$  indicate the net increase share of employment, asset, and output, respectively.

*Step 3.* To calculate the share of industry  $i$  in city  $c$  in different dimensions, the final industrial dynamic agglomeration index in three dimensions could be obtained as

$$\begin{aligned} \text{density\_adl}_{ct} &= \sum_i ada_{cit} * sl_{cit}, \\ \text{density\_ada}_{ct} &= \sum_i ada_{cit} * sa_{cit}, \quad \text{and,} \\ \text{density\_ado}_{ct} &= \sum_i ado_{cit} * so_{cit}, \end{aligned} \quad (16)$$

in which  $sl_{cit}$ ,  $sa_{cit}$  and  $so_{cit}$  indicate the total share of employment, asset, and output, respectively.

In addition to the database of night light data and LandScan global population dynamics data, China industrial enterprise database and China City Statistical Yearbook are used to calculate the indicator.

*4.3. Spatial Estimation Model.* There are spatial correlations among neighboring regions according to the "First Law of Geography," and ignoring spatial factors may lead to deviations in empirical results. We use Moran index to test the spatial correlation of cities, and Table 1 gives the results of estimation. It could be found that there is positive spatial correlation among the cities from 2000 to 2013.

In general, we intend to measure regional coordination from the perspective of spatial convergence. We rejected the hypothesis that the spatial Durbin model could be simplified to spatial lag model or spatial error model by LR test. Therefore, the spatial Durbin fixed effects model is used as the baseline regression equation combined with Hausmann test. The equation is formed as

$$\text{Lnlt}_{it} - \text{Lnlt}_{it-1} = \lambda W_n (\text{Lnlt}_{it} - \text{Lnlt}_{it-1}) + \gamma \text{Lnlt}_{it-1} + \beta \text{Lnspawl}_{it} + \theta W_n * \text{Lnspawl}_{it} + \gamma \text{LnX}_{it} + \eta W_n \text{LnX}_{it} + \mu_i + \zeta_t + \xi_{it}, \quad (17)$$

in which  $\text{Lnlt}_{it}$  is indicated as night light data,  $\text{Lnspawl}_{it}$  is used to represent urban sprawl, and  $X_{it}$  are other control variables.  $\mu_i$  and  $\zeta_t$  represent the fixed effects of cities and time, and  $\xi_{it}$  is random error term. Particularly,  $W_n$  could be separated into three dimensions of weight matrix, including space weight matrix of adjacency space, physical distance, and economic distance. The construction of the adjacent space weight matrix is related to whether the cities are adjacent to each other. If two cities are adjacent to each other, the weight is assigned to 1, or it is 0. Although the adjacent space weight matrix has been widely used in spatial econometric analysis, the assumption that there is no correlation among nonadjacent cities is rather not reasonable. Therefore, this paper takes the reciprocal of the shortest road distance between the two cities as the weight of the spatial matrix, so as to further measure the location relationship among the cities. The formula could be written as  $w_{ij}^d = 1/d_{ij}$ . It is worth noting that the space weight matrix of physical distance ignored the economic connection among the cities. The spatial connection among the cities is not only related to distance or whether they are adjacent, but also related to the economic ties. The space weight matrix of economic distance could be written as

$$w_{ij}^e = w_{ij}^d \text{diag}\left(\frac{\bar{Y}_1}{\bar{Y}}, \frac{\bar{Y}_2}{\bar{Y}}, \dots, \frac{\bar{Y}_n}{\bar{Y}}\right), \quad (18)$$

in which  $w_{ij}^d$  is the space weight matrix of physical distance, and  $\bar{Y}_i$  is the average value of city lights, which could be written as  $\bar{Y}_i = 1/(T_{\max} - T_{\min} + 1) \sum_{T_{\min}}^{T_{\max}} Y_i$ .  $\bar{Y}$  is the unique average value of city lights, which could be written as  $\bar{Y} = 1/n(T_{\max} - T_{\min} + 1) \sum_{i=1}^n \sum_{T_{\min}}^{T_{\max}} Y_i$ .

$X_{it}$  indicates the other control variables that affect economic coordination, such as savings rate. We take the compound expression of  $(n + g + d)$  as the control variable according to (Yu [23]), in which  $n$  represents the population growth rate,  $g$  represents technological progress rate, and  $d$  represents depreciation rate. The calculation method of technological progress rate and depreciation rate is reported in Appendix. In addition, according to Xie and Wang [28], the construction of road infrastructure could influence the spatial distribution of firms, and the interdistrict transportation infrastructure connecting cities could promote the flow of production factors among the regions, thus promoting the coordinated development of regions. So, we take paved road area per capita to measure the level of road infrastructure. Meanwhile, due to the research of Yuan and Zhu [29], smart city is evaluated from three dimensions of information, human capital, and urban innovation activity. Limited to data availability, we take telecom business income as the index of cities' promotion of information technology and take the number of college students per ten thousand population to evaluate the level of human capital. In ad-

TABLE 1: Spatial correlation test.

year	Moran's I value	year	Moran's I value
2000	0.312*** (6.021)	2007	0.232*** (8.066)
2001	0.211*** (8.921)	2008	0.215** (2.014)
2002	0.212*** (7.321)	2009	0.202*** (5.054)
2003	0.243*** (2.832)	2010	0.205*** (2.811)
2004	0.258*** (6.031)	2011	0.208*** (5.587)
2005	0.206*** (7.067)	2012	0.366*** (9.054)
2006	0.218*** (7.954)	2013	0.404*** (9.065)

\*\*\*, \*\*, and \* indicate significance at the 1%, 5%, and 10% level. Z values are reported in parentheses.

dition, Kou and Liu released the report of China's urban and industrial innovation, so that we could adopt the data to measure the level of urban innovation. The interactive items of three indicators are built to evaluate the construction of smart cities. Table 2 shows the statistical description of related variables.

## 5. Empirical Test

**5.1. Baseline Regression Results.** Table 3 presents the baseline results on how urban sprawl affects economic coordination, where  $\text{Lnlt}_{it-1}$  (Impact) is used to indicate the variable of  $\text{Lnlt}_{it-1}$  after introducing control variables. The result shows that the value of the coefficient  $\text{Lnlt}_{it-1}$  (Impact) increased significantly after introducing the variable of sprawl, indicating that the process of urban sprawl is beneficial to regional coordination. In addition, the value of  $\text{Lnlt}_{it-1}$  coefficient is the largest corresponding to the adjacent space weight matrix, indicating that the economic synergy among adjacent cities is stronger. Furthermore, the value of the coefficient  $\text{Lnlt}_{it-1}$  corresponding to the adjacent space weight matrix showed most obvious change under the impact of urban sprawl, reflecting more significant convergence among neighboring cities. However, the corresponding  $W * \text{Lnsprawl}_{it}$  coefficient is significantly negative, indicating that the spatial spread of neighboring cities is not conducive to their own growth, which shows vicious competitive relationship.

**5.2. Regression Results Based on Smart City Construction.** Table 4 shows the regression result based on smart city construction. We adopt the variable of  $\text{Lnsmart}_{it}$  to indicate smart city construction, which is the interactive items of  $\text{Lninformation}$ ,  $\text{Lnlabor}$ , and  $\text{Lninnovation}$ . In addition, the result is reported under the condition of space weight matrix of economic distance. Different from the baseline result, the absolute value of coefficient  $\text{Lnlt}_{it-1}$  shows decreasing trend after considering the influence of smart city construction, indicating that smart city construction is not conducive to promotion of economic coordination. However, smart city construction could promote regional economic growth due to the positive coefficient of  $\text{Lnsmart}_{it}$ . The interaction terms of urban sprawl and smart city construction are introduced to test the interactive effect. The result shows that the absolute value of coefficient  $\text{Lnlt}_{it-1}$  has been greatly improved after introducing the interactive item. In addition, the negative coefficient of  $\text{Lnsprawl}_{it}$  and positive coefficient of

$\text{Lninteraction}_{it}$  indicate that urban sprawl is not conducive to regional economic growth but shows positive effect through the interaction with smart city construction. The comparison among the results suggests that the conditions of interaction between urban sprawl and smart city construction could promote regional coordination, and the process of smart city construction could reduce the negative effect on economic growth, which is consistent with theoretical mechanism. Moreover, vicious competitive relationship still exists due to the negative value of  $W * \text{Lninteraction}_{it}$ .

**5.3. Robustness Test.** Suburbanization index is used to test the robustness of empirical results according to Liu et al. [2]. The method of suburbanization index is measured by the proportion of the population, which is three kilometers away from downtown. This paper takes night light data to identify the city center and delimits the three-kilometer range. Meanwhile, Landscan dataset is used to extract areas that include the lighting threshold and population density at the same time, so as to measure the level of suburbanization. Table 5 presents the robustness test, which shows no different conclusion from baseline result. The result suggests that the suburbanization could promote regional coordination. What needs to be emphasized is the negative effect on economic growth, which is more significant for suburbanization. The reason lies in that the calculation method of suburbanization emphasizes the expansion of land or population, especially excluding areas within three kilometers of the city center. However, smart city construction reduced the negative effect on economic growth and could impact positive effect on regional coordination.

**5.4. Endogenous Processing.** Although the spatial model could reduce the endogenous error by introducing spatial weight matrix, the generalized spatial two-stage least square method is used to deal with the endogenous term in order to avoid the deviation caused by the possible mutual influence between urban sprawl and economic growth. According to Burchfield et al. [30], in the areas with more uneven terrain, the difficulty of spatial expansion is increasing. Therefore, we use the reciprocal of urban surface roughness as an instrumental variable for urban sprawl. The surface roughness is obtained from the national urban digital elevation data, and the urban surface raster is extracted by Arc GIS software. The urban surface roughness could be obtained by

TABLE 2: Statistical description of related variables.

Variables	Sample size	Mean value	Minimum value	Maximum value	Standard deviation
Lnlt	3696	1.669	-1.790	4.781	1.172
Lnsprawl	3696	-0.856	-1.649	-0.268	0.219
Lnagg	3696	5.360	0.018	10.450	1.358
Lnngd	3696	-1.890	-7.142	-0.168	0.735
Lns	3696	-0.595	-1.115	-0.199	0.215
Lnroad	3696	1.961	-1.966	4.686	0.642
Lninformation	3696	12.289	10.044	15.554	0.845
Lnlabor	3696	-4.017	-6.986	-1.476	1.059
Lninnovation	3696	-0.733	-4.605	6.503	1.811

TABLE 3: Effect of urban sprawl on economic coordination.

Matrix classification	OLS	Adjacent space weight matrix	Space weight matrix of physical distance	Space weight matrix of economic distance
$Lnlt_{it-1}$	-0.014*** (-4.31)	-0.072*** (-8.60)	-0.067*** (-7.62)	-0.063*** (-7.59)
$Lnlt_{it-1}$ (impact)	-0.013*** (-3.85)	-0.076*** (-7.96)	-0.070*** (-5.79)	-0.065*** (-7.27)
$Lnsprawl_{it}$	0.023*** (6.42)	0.012* (1.88)	0.008 (1.19)	0.002 (0.34)
$Lns_{it}$	0.013 (1.58)	0.002** (2.52)	0.002** (2.54)	0.002*** (2.91)
$Ln(n+g+d)_{it}$	0.004*** (4.09)	0.019** (2.25)	-0.009 (-0.95)	0.004 (0.72)
$W * Lnsprawl_{it}$		-0.022** (-2.04)	-0.014 (-1.13)	0.046** (2.48)
$W * Lns_{it}$		0.002 (1.51)	0.002 (1.19)	-0.001 (-0.26)
$W * Ln(n+g+d)_{it}$		-0.021** (-2.07)	0.013 (1.04)	0.084*** (5.21)
Fixed effects	Yes	Yes	Yes	Yes
$\lambda$		0.553*** (24.59)	0.604*** (26.28)	0.145*** (3.67)
$R^2$	0.229	0.706	0.691	0.611
Observations	3696	3696	3696	3696

\*\*\*, \*\*, and \* indicate significance at the 1%, 5%, and 10% level. Z values are reported in parentheses.

TABLE 4: Effect of smart city construction on economic coordination.

Variable	Impact of smart city	Impact of urban sprawl	Impact of interaction
$Lnlt_{it-1}$	-0.063*** (-7.59)	-0.063*** (-7.59)	-0.063*** (-7.59)
$Lnlt_{it-1}$ (impact)	-0.062*** (-7.56)	-0.065*** (-7.27)	-0.066*** (-7.38)
$Lnsmart_{it}$	0.001* (1.78)		0.002 (1.54)
$Lnsprawl_{it}$		-0.002 (-0.34)	-0.004* (-1.91)
$Lninteraction_{it}$			0.0006* (1.72)
$W * Lnsmart_{it}$	-0.0007** (-2.31)		-0.001* (-1.68)
$W * Lnsprawl_{it}$		0.046** (2.48)	-0.015 (-0.66)
$W * Lninteraction_{it}$			-0.0002*** (-3.21)
Control variable	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes
$\Lambda$	0.156*** (4.56)	0.145*** (3.67)	0.136*** (2.67)
$R^2$	0.702	0.611	0.543
Observations	3696	3696	3696

\*\*\*, \*\*, and \* indicate significance at the 1%, 5%, and 10% level. Z values are reported in parentheses.

measuring the standard deviation of the surface slope. Meanwhile, we take one period lagged smart city construction to reduce the endogenous error. Table 6 represents the endogenous processing result, suggesting that the

economic coordination under the effect of urban surface roughness is more obvious compared with the coefficient of  $Lnsprawl_{it}$ . In addition, the interaction between urban sprawl and smart city construction is conducive to economic

TABLE 5: Robustness test.

Variable	Impact of smart city	Impact of suburbanization	Impact of interaction
$\text{Lnlt}_{it-1}$	-0.063*** (-7.59)	-0.063*** (-7.59)	-0.063*** (-7.59)
$\text{Lnlt}_{it-1}$ (impact)	-0.062*** (-7.56)	-0.065*** (-7.27)	-0.068*** (-5.76)
$\text{Lnsmart}_{it}$	0.001* (1.78)		0.001* (1.88)
$\text{Lnsuburbanization}_{it}$		-0.013*** (-3.62)	-0.011*** (-2.91)
$\text{Lninteraction}_{it}$			0.006* (1.73)
$W * \text{Lnsmart}_{it}$	-0.0007*** (-2.31)		-0.003 (-1.09)
$W * \text{Lnsuburbanization}_{it}$		-0.013 (-1.32)	-0.009*** (-2.04)
$W * \text{Lninteraction}_{it}$			-0.003 (-1.26)
Control variable	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes
$\Lambda$	0.107*** (2.89)	0.113*** (2.87)	0.116*** (2.12)
$R^2$	0.609	0.612	0.601
Observations	3696	3696	3696

\*\*\*, \*\*, and \* indicate significance at the 1%, 5%, and 10% level. Z values are reported in parentheses.

TABLE 6: Endogenous processing result.

Variable	Impact of smart city	Impact of urban sprawl	Impact of interaction
$\text{Lnlt}_{it-1}$	-0.063*** (-7.59)	-0.063*** (-7.59)	-0.063*** (-7.59)
$\text{Lnlt}_{it-1}$ (impact)	-0.060*** (-8.45)	-0.064*** (-7.37)	-0.065*** (-7.16)
$\text{Lnsmart}_{it-1}$	0.001*** (2.36)		0.001* (1.91)
$\text{Lnroughness}_{it}$		0.003* (1.83)	-0.002 (-1.21)
$\text{Lninteraction}_{it}$			0.011* (1.66)
$W * \text{Lnsmart}_{it-1}$	-0.001*** (-2.32)		-0.001 (0.75)
$W * \text{Lnroughness}_{it}$		-0.007*** (-2.28)	-0.004* (-1.66)
$W * \text{Lninteraction}_{it}$			-0.008*** (-2.21)
Control variable	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes
$\lambda$	0.145*** (4.42)	0.145*** (3.67)	0.142*** (2.67)
$R^2$	0.609	0.611	0.610
Observations	3696	3696	3696

\*\*\*, \*\*, and \* indicate significance at the 1%, 5%, and 10% level. Z values are reported in parentheses.

growth, as well as coordination, which is consistent with baseline result.

## 6. Further Research

Some studies have shown that urban sprawl tends to restrict economic growth through changing the level of industrial agglomeration but ignored the effect of construction of smart city (Liangfeng and Li, [31]). According to the studies, urban sprawl weakened the effect of industrial

agglomeration by expanding the scope of space. However, it could be expected that smart city construction could reduce the negative effect of space expansion. We incorporate the geographic change into the construction of agglomeration index, in order to reflect the impact of urban sprawl. We introduce the variables and interactive items to test the interactive effect of industrial agglomeration, urban sprawl, and smart city construction on regional coordination. The benchmark model is revised to the following equation:

$$\text{Lnlt}_{it} - \text{Lnlt}_{it-1} = \lambda W_n (\text{Lnlt}_{it} - \text{Lnlt}_{it-1}) + \gamma \text{Lnlt}_{it-1} + \beta \text{Lnsprawl}_{it} + \kappa \text{Lnagg}_{it} + \varphi \text{Lnsprawl}_{it} * \text{Lnagg}_{it} + \mu_i + \zeta_t + \xi_{it}. \quad (19)$$

The result presented in Table 7 shows that the absolute value of  $\text{Lnlt}_{it-1}$  has been reduced to a certain extent, when introducing the impact of the dynamic industrial agglomeration. It implies that the regions with higher economies are more attractive to the industrial inflows. In addition, the smart city construction tends to widen the gap among the regions. The reasonable explanation lies in that smart city construction could accelerate the flow of factors and attract

high quality resources in more developed areas. Meanwhile, the interaction term of  $\text{Lnsprawl}_{it} * \text{Lnagg}_{it}$  is negative, indicating that the sprawling urban structure weakens the industrial agglomeration effect, which also has attached negative impact on economic growth. The reason lies in that the mismatch between the land supply and factors inflow in the eastern and central western cities has provided reasonable explanation for the result (Lu et al. [32]). The faster

TABLE 7: Mediation effect test from dynamic industrial agglomeration.

Variable	Impact of industrial agglomeration	Interaction effect of smart city construction and agglomeration	Interaction effect of urban sprawl and agglomeration	Interaction effect of triple factors
$\text{Lnlt}_{it-1}$	-0.063*** (-7.59)	-0.063*** (-7.59)	-0.063*** (-7.59)	-0.063*** (-7.59)
$\text{Lnlt}_{it-1}$ (impact)	-0.062*** (-6.09)	-0.061*** (-4.92)	-0.062*** (-4.06)	-0.064*** (-3.98)
$\text{Lnagg}_{it}$	0.002** (2.37)	0.001 (1.50)	0.001 (1.37)	0.001 (1.10)
$\text{Lnsmart}_{it}$		0.001* (1.71)		0.001 (1.22)
$\text{Lnsprawl}_{it}$			-0.004* (-1.91)	-0.002 (-1.54)
$\text{Lninteraction}_{it}$		0.0006* (1.82)	-0.007 (-1.06)	0.0003* (1.75)
$W * \text{Lnagg}_{it}$	-0.002 (-1.28)	-0.001 (-1.58)	-0.001 (-1.51)	-0.001* (-1.83)
$W * \text{Lnsmart}_{it}$		-0.001** (-1.98)		0.001* (1.66)
$W * \text{Lnsprawl}_{it}$			0.001 (1.09)	0.001* (1.66)
$W *$		-0.0004 (-0.87)	0.0001** (2.21)	0.0001* (1.77)
$\text{Lninteraction}_{it}$				
Control variable	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes
$\lambda$	0.152** (2.56)	0.135*** (2.67)	0.102** (2.03)	0.187** (2.34)
$R^2$	0.521	0.598	0.534	0.492
Observations	3696	3696	3696	3696

\*\*\*, \*\*, and \* indicate significance at the 1%, 5%, and 10% level. T values are reported in parentheses.

TABLE 8: Depreciation rates in different provinces.

Region	Depreciation rate	Region	Depreciation rate (%)
Beijing	9.90	Henan	10.85
Tianjin	10.10	Hubei	10.38
Hebei	10.66	Hunan	9.58
Shanxi	10.28	Guangdong	10.08
Inner Mongolia	10.37	Guangxi	10.49
Liaoning	10.46	Hainan	9.36
Jilin	11.49	Chongqing	9.19
Heilongjiang	10.46	Sichuan	9.53
Shanghai	10.06	Guizhou	9.57
Jiangsu	11.49	Yunnan	9.29
Zhejiang	10.33	Shanxi	9.50
Anhui	10.38	Gansu	9.95
Fujian	10.14	Qinghai	9.46
Jiangxi	10.78	Ningxia	10.36
Shandong	10.93	Average	10.19

TABLE 9: Result of stochastic frontier model.

Variable	Coefficient	Regression	Variable	Coefficient	Regression
$\text{ln}L_{it}$	$\beta_1$	0.132*** (0.011)	$\text{tln}L_{it}$	$\beta_8$	0.003*** (0.000)
$\text{ln}K_{it}$	$\beta_2$	-0.455*** (0.016)	$\text{tln}K_{it}$	$\beta_9$	-0.017*** (0.001)
$T$	$\beta_3$	0.018*** (0.003)	$\sigma^2$		0.001*** (0.000)
$(\text{ln}K_{it})^2$	$\beta_4$	0.385*** (0.062)	$\eta$		0.025*** (0.003)
$(\text{ln}L_{it})^2$	$\beta_5$	0.003*** (0.001)	$\gamma$		0.698*** (0.018)
$t^2$	$\beta_6$	0.001*** (0.000)	Log likelihood		8.979
$\text{ln}K_{it}\text{ln}L_{it}$	$\beta_7$	-0.079*** (0.011)	Log likelihood-ratio test of $\text{sigma-u} = 0$		7908

\*\*\*, \*\*, and \* indicate significance at the 1%, 5%, and 10% level. Standard deviation values are reported in parentheses.

land supply in the western region weakened the agglomeration effect, which further increased the regional disparity. The interaction of triple factors shows positive effect on economic growth, as well as regional coordination. The reason lies in that smart city construction tends to accelerate the flow of factors, while urban sprawl could weaken the boundary effect created by the distance among the cities.

## 7. Conclusion and Policy Implications

The rapid improvement in urbanization has promoted discontinuous and low-density spatial expansion. Smart city construction has become an important driving force for the development of urbanization in China. This paper takes the objective and corrected urban night light data as proxy variable of economic growth, combined with LandScan global population dynamics statistics to measure the level of urban sprawl. It is found that urban sprawl is conducive to promoting the coordinated development, which is more obvious among neighboring cities. Further research shows that smart city construction is conducive to economic growth other than regional coordination. The endogenous treatment using urban surface roughness as instrumental variable shows no significant difference. Further research shows that smart city construction together with urban sprawl and dynamic industrial agglomeration could promote economic growth, as well as regional coordination.

The findings are relevant from public policy. The empirical result shows that urban sprawl could strengthen coordination among neighboring cities, but vicious competition relationship restricts the process. Meanwhile, smart city construction is beneficial to economic growth, but not for other cities. There is amount of evidence showing that the formation of the smart infrastructure network has gradually blurred the geographical boundaries among the cities but highlighted the existence of administrative barriers (Tang [33]). Therefore, it is necessary to promote the infrastructure construction, and to explore the feasibility of integrated administration on the basis of integrated infrastructure. The government should strengthen the construction of cooperation mechanism in the process of integration in physical

space and promote the coordinated development among the regions.

The policy implications also lie in improving the market mechanism and continue to deepen the regional coordinated strategy. The empirical results show that there is disconnection between urban sprawl and industrial agglomeration, which is not conducive to economic growth and regional coordination. It suggests that the government should deepen the regional coordinated development strategy, improve the market mechanism, and optimize the land supply structure, so as to promote the coordinated relationship of urban sprawl and industrial agglomeration, in addition to accelerating the cross-regional flow of factors through the construction of smart cities.

## Appendix

### A. Depreciation rate

Limited by the availability of data, it is difficult to obtain the depreciation rates at the city level. However, taking the same depreciation rate for all cities tends to cause additional error. Therefore, we estimate depreciation rates at the provincial level and take the same value for cities in the same province. According to the “Depreciation Period Table of Fixed Assets of State-owned Enterprises,” we set the depreciation periods of the construction industry and production equipment as forty years and sixteen years, respectively. It is conventionally assumed that the residual value rate of fixed assets is 5%, and the geometric decline calculation formula is specifically expressed as  $w_\tau = (1 - \delta)^\tau$ , in which  $\tau = 0, 1, 2, \dots, T$ . The total depreciation rate of each province could be calculated by multiplying the depreciation rate by the corresponding investment weight of construction industry and production equipment. Table 8 shows the result of depreciation rates in different provinces.

### B. Technological Progress Rate

We adopt the stochastic frontier model to measure technological progress rate, which could be expressed as transcendental logarithmic production function:

$$\ln Y_{it} = \beta_0 + \beta_1 \ln L_{it} + \beta_2 \ln K_{it} + \beta_3 t + 0.5\beta_4 (\ln K_{it})^2 + 0.5\beta_5 (\ln L_{it})^2 + 0.5\beta_6 t^2 + \beta_7 \ln K_{it} \ln L_{it} + \beta_8 t \ln L_{it} + \beta_9 t \ln K_{it} + v_{it} - u_{it}. \quad (\text{B.1})$$

in which  $Y$  is the cities' total output,  $L$  indicates the labor force, and  $K$  is the cities' capital stock. Both  $Y$  and  $L$  could be collected in the Statistical Yearbook of Chinese cities, while the capital stock of cities needs to be measured. Perpetual inventory method is used for calculation of capital stock.

(Table 9) shows the regression results of stochastic frontier model, and the technological progress rate could be calculated by equation (B.2).

The total factor productivity, as well as the decomposition indices of scale efficiency, rate of technological

progress, and technological efficiency could be calculated, using Kumbhakar and Lovell's decomposition method, which is expressed as follows:

$$FTP_{it} = \beta_3 + \beta_6 t + \beta_8 \ln L_{it} + \beta_9 \ln K_{it}. \quad (\text{B.2})$$

## Data Availability

The underlying data could be found at <https://ngdc.noaa.gov/eog/dmsp/downloadV4composites.html>. In addition, China industrial enterprise database and China City Statistical Yearbook are used for empirical test. The data could be required through e-mail address: haousts@usts.edu.cn.

## Conflicts of Interest

The authors declare that they have no conflicts of interest.

## Acknowledgments

This work was supported by the Major Project of National Philosophy and Social Science Foundation of China under Grant No. 18ZDA038 and the Project of National Philosophy and Social Science Foundation of Jiangsu Province, China, under Grant No. 20GLC014.

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